The Effectiveness of Remedial Courses in Italy: A Fuzzy Regression Discontinuity Design

Maria De Paola, Vincenzo Scoppa

Department of Economics, Statistics and Finance, University of Calabria

FEDEA Workshop on "Remedial Education in Europe"

Madrid, 19th January 2017

Introduction

- In tertiary education, remedial courses in basic skills such as mathematics, reading comprehension, writing, should enable low-ability students to begin their university career with an adequate level of skills
- About one-third of US university students are required to take remedial courses
- An increasing number of Universities in Europe offer remedial programs
- Many Italian Universities, at the beginning of each academic year, organize courses at the pre-university level

Remedial courses are controversial

- They drain resources, both in terms of money and time, towards students who appear not well-suited for college

- Placement into remediation may negatively impact student outcomes due to social stigma and negative effects on self-esteem and educational expectations

Econometric Problems in Evaluating the Impact

- Not clear evidence on the effectiveness of remedial courses

Thorny econometric problems in evaluating their impact:

- The assignment of students to these courses is not random: typically, lower ability students are required to attend them
- Students with (unobservable) high motivation could attend remedial courses (causing an upward bias in estimation),
- or, alternatively, remedial courses could be taken only by students with worse perspectives (risk of downward bias)

Literature Review

- Bettinger-Long (2009) analyze the effect of remediation in Ohio using an instrumental variable strategy, which relies on the importance of distance from university for student's college choice combined to the fact that remediation assignment rules differ across universities

- Martorell-McFarlin (2011) and Calcagno-Long (2008) undertake an estimation strategy based on a RDD exploiting the fact that in the States they consider (Texas and Florida), assignment to remediation is decided on the basis of the score students obtain in a placement exam
- Evidence of little effects on a wide range of educational and labor market outcomes

- A number of other works analyze remedial programs at primary or secondary schools (Lavy-Schlosser (2005); Jacob-Lefgren (2004), etc. They found typically positive effects

Institutional Setting

- To evaluate the effects of remedial courses on the achievement of college students
- We take advantage of a project, financed by the Regione Calabria using European Social Fund, involving 4,019 students enrolled in the academic year 2009-2010 at the University of Calabria, a medium sized Public University located in the South of Italy

- The project was aimed at improving students' basic competences through an intensive program (for a total of 160 hours) offering a number of courses in subjects such as mathematics and language skills

- Remedial courses in 5 different Fields of Study (Economics&Business; Pharmacy; Pol. Sciences; Math&Sciences; Humanities)

Placement test and assignment to remediation

- Assignment to remedial courses was based on the results obtained by the students at a placement test

- In each field of study, students performing below a certain cutoff score were required to enroll in the remedial courses

- We build a variable, $\textit{Test Score}_i$, as the percentage of correct answers given by student *i* in the placement test

- To make homogeneous students' scores across fields of study we subtract the threshold level fixed by each Department Board to assign students to remediation
- Test Score is our "forcing" or "running" variable

Assignment to remediation

- A positive Test Score indicates that the student is placed above the threshold and he/she is not required to attend the remedial courses,
- while a score of 0 or a negative score indicates that the student is below the threshold and should attend the remedial courses

- We define the dummy variable *Assigned Treatment*, which takes the value of one if student *i* has been assigned to the remedial courses and zero otherwise

Remedial Courses

- Organized in small classes with qualified instructors.
- College courses for all the students started only after the ending of the remedial courses
- Remedial courses do not confer any academic credit
- Students assigned to treatment were highly recommended to attend the courses, but attendance was not compulsory
- We build the variable *Effective Treatment*$_i$ as the number of hours of remedial courses attended by student *i*

Differences wrt. other studies

Compared to similar works investigating the effects of remediation in US, we take advantage of the fact that:

- Students have no incentives in trying to avoid to be placed under remediation
- Students could not retake the placement test
- We measure very precisely the intensity of the treatment, as we know the exact number of hours attended by each student
- Students are not allowed to change their Field of Study after the placement test or after remedial courses
- In the first two academic years, students have compulsory courses, with very little choice

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Assigned Treatment	4019	0.608	0.488	0	1
Effective Treatment	4019	49.813	62.553	0	160
Treatment: 80% of hours	4019	0.342	0.474	0	1
Test Score	4019	-1.978	14.796	-50	46.835
Credits	4019	46.369	38.759	0	126
Drop-out	4019	0.237	0.426	0	1
Average Grade	3013	23.931	2.710	18	30
Female	4019	0.647	0.478	0	1
High School Grade	4019	81.586	11.616	60	100
Lyceum	4019	0.487	0.500	0	1
Late Enrolment	4019	0.238	0.426	0	1
Field: Economics	4019	0.307	0.461	0	1
Field: Pharmacy	4019	0.152	0.359	0	1
Field: Humanities	4019	0.239	0.427	0	1
Field: Math and Sciences	4019	0.150	0.357	0	1
Field: Political Sciences	4019	0.152	0.359	0	1

Variable	Assigned to Treatment		Control	
	Mean	Std. Dev.	Mean	Std. Dev.
Effective Treatment	81.020	61.940	1.438	13.469
Treatment: 80% of hours	0.557	0.497	0.009	0.094
Test Score	-11.387	8.748	12.608	9.466
Credits	40.074	36.487	56.126	40.145
Drop-out	0.261	0.439	0.201	0.401
Average Grade	23.193	2.529	24.974	2.614
Female	0.680	0.466	0.596	0.491
High School Grade	79.022	11.122	85.560	11.245
Lyceum	0.410	0.492	0.608	0.488
Late Enrolment	0.252	0.434	0.216	0.412
Observations	2443		1576	

Empirical strategy

- To estimate the causal effect of remedial courses on student's performance we use a Fuzzy Regression Discontinuity Design

- Measures of Performance (after two academic years): Number of Credits, Probability of Dropping Out, Average Grade at Exams

- We exploit the fact that the assignment to the treatment has been defined as a discontinuous function of the *Test Score* obtained by the student at the placement test

- Due to some randomness in the Test Score ("forcing variable”) in the neighborhood of the cutoff, students below or above the threshold are very similar

- Even if the test score is correlated to student academic achievement, the relationship should be smooth with no jump in the proximity of the cutoff

- Therefore, any jump in the outcome near the cutoff can be interpreted as evidence of a treatment effect

Students' Participation in the Program: Imperfect Compliance

Compliance of students to the assignment was not perfect:

- Some of the students assigned to the treatment have taken 0 hours or a reduced number of hours

81 (out of 160) is the avg. number of hours attended by students assigned to the treatment; 55% of these students attended at least 80% of hours

- A few students who were assigned to the Control group (not required to take remedial courses) decided to attend the courses

Instrumental Variables Estimation

To deal with endogeneity problems we follow an Instrumental Variable estimation strategy using the assignment to the treatment as an instrument for the effective participation in the courses.

We estimate with Two-Stage-Least Squares the following model:

$$EffectiveTreatment_i = \phi_0 + \phi_1 AssignedTreatment_i + \phi_2 g\left(Test\ Score_i\right) + \phi_3 X_i + \mu_k + \upsilon_i$$

$$Y_i = \beta_0 + \beta_1 EffectiveTreatment_i + \beta_2 f\left(Test\ Score_i\right) + \beta_3 X_i + \mu_k + \varepsilon_i$$

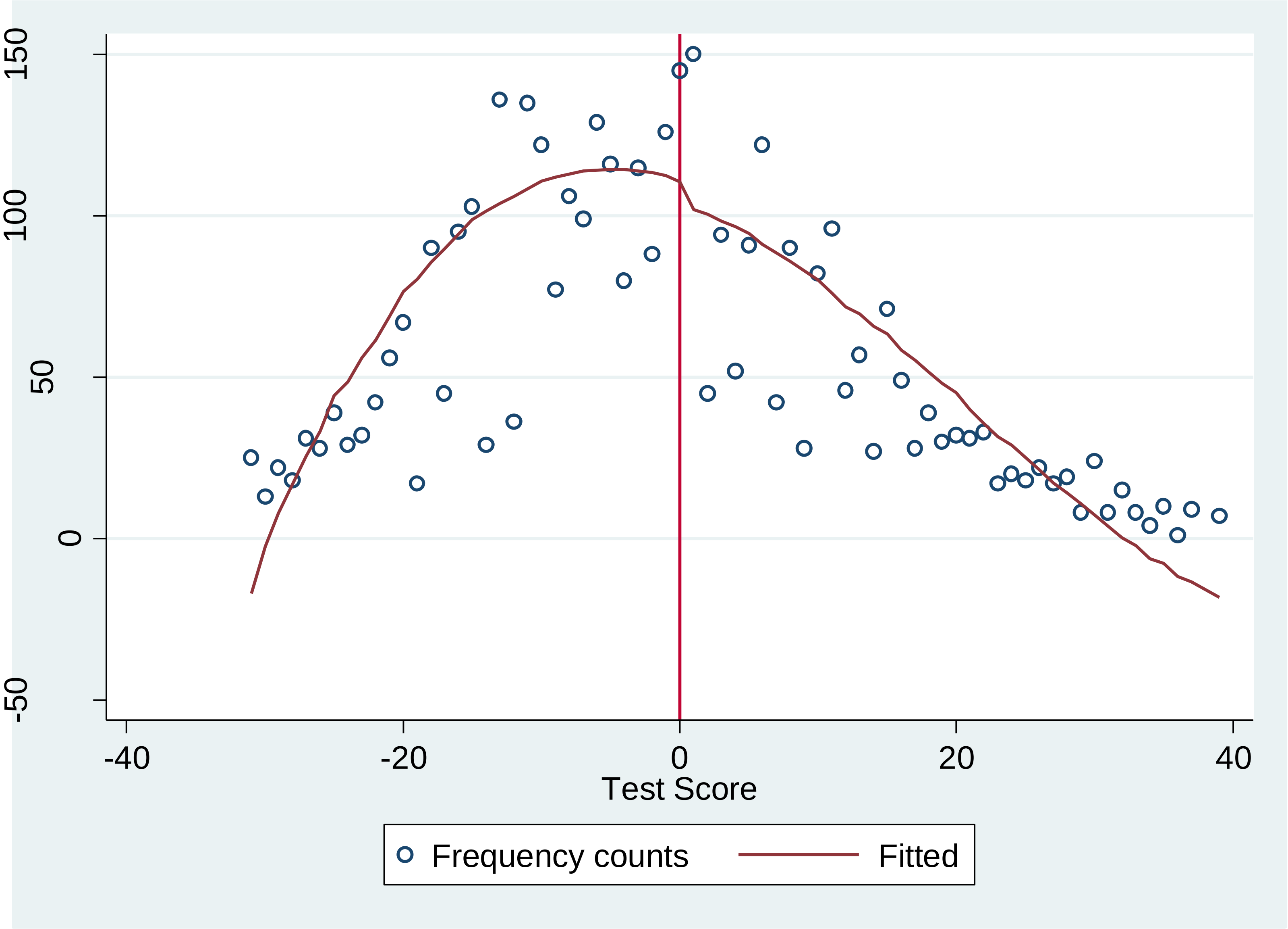
Checks for random assignment around the discontinuity

We firstly investigate whether observable characteristics vary discontinuously around the cutoff

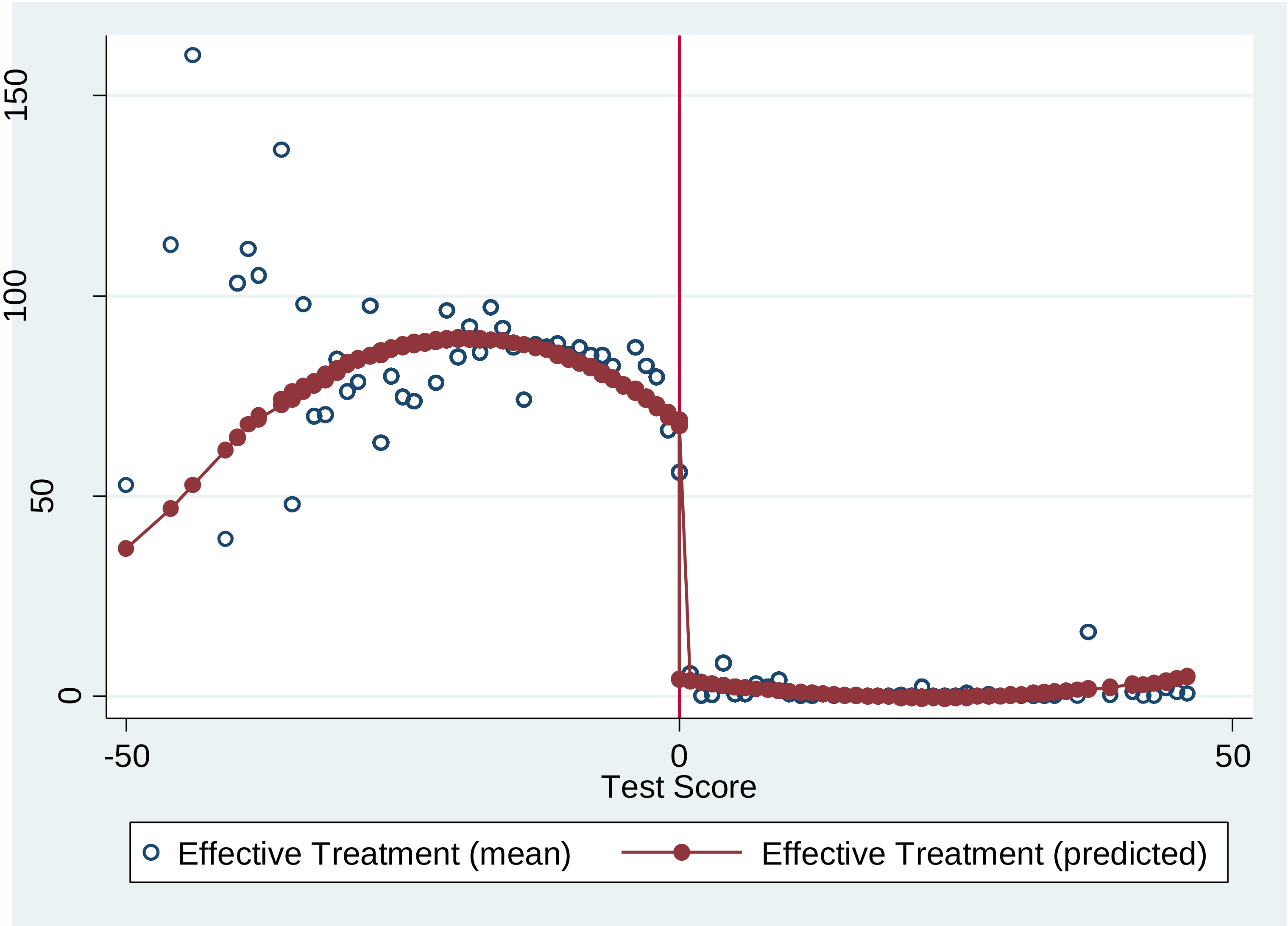
Differences in pre-determined characteristics. RDD estimates

	(1)	(2)	(3)	(4)
	Female	High School G.	Lyceum	Late Enr.
Assigned Treatment	0.015 (0.028)	-0.129 (0.658)	0.095** (0.030)	-0.012 (0.026)
Obs.	4019	4019	4019	4019
LOCAL WINDOW				
Assigned Treatment	0.045 (0.052)	1.271 (1.264)	0.032 (0.059)	-0.012 (0.050)
Obs.	1178	1178	1178	1178

Discontinuity in the Density of Test Score?



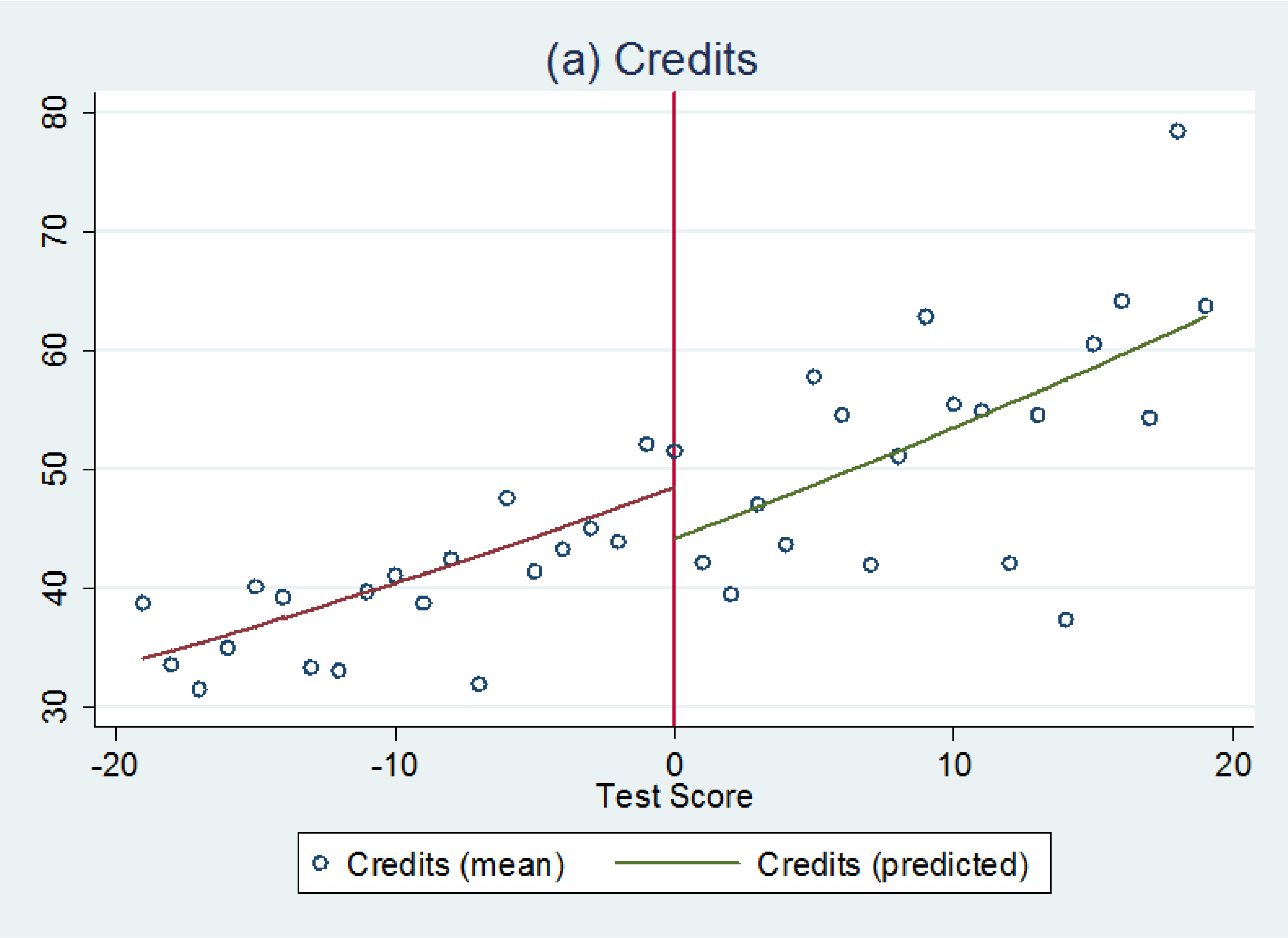
First Stage: Test Score and Hours of Remedial Courses



Estimation Results (TSLS): The Impact of Remedial Courses on Credits

Panel A: Two-Stage Least Squares Estimates				
Hours Rem. Courses/100	6.463*	5.881**	6.794***	7.596**
	(3.904)	(2.543)	(2.540)	(3.282)
Polynomial of Test Score	First order	First order	Second order	Third order
Controls	NO	YES	YES	YES
Observations	4019	4019	4019	4019
Panel B: First Stage				
Assigned Treatment	0.513***	0.535***	0.461***	0.453***
	(0.081)	(0.051)	(0.046)	(0.033)
Panel C: Intention To Treat Effects				
Assigned Treatment	4.471*	4.087**	4.728***	4.881**
	(2.481)	(1.779)	(1.779)	(2.126)

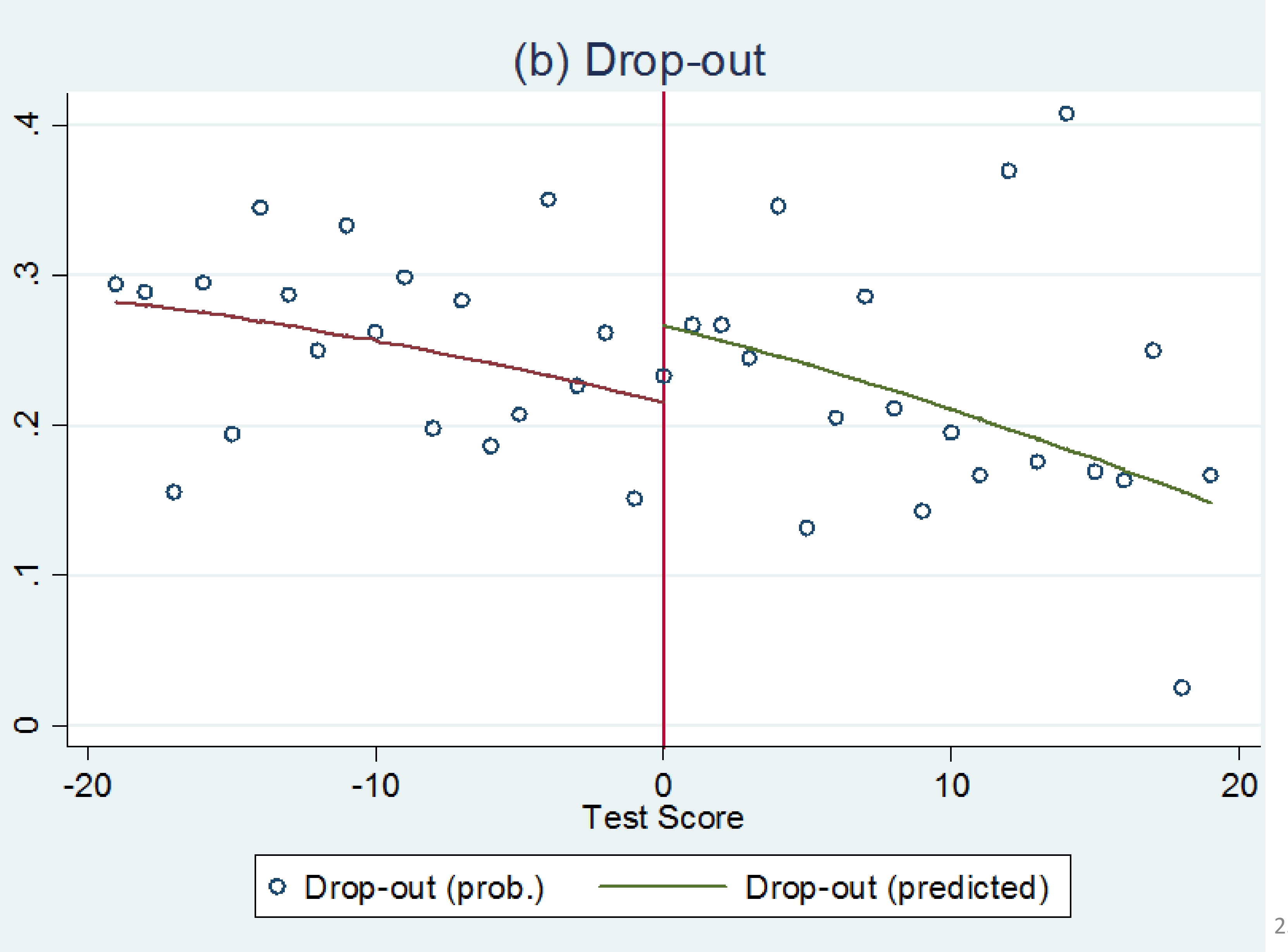
The impact of Remedial Courses on Credits



Estimation Results (TSLS): The Impact of Remedial Courses on Drop-out

	(1)	(2)	(3)	(4)
Two-Stage Least Squares Estimates				
Hours Rem. Courses/100	-0.0629*	-0.0730**	-0.0914**	-0.134**
	(0.036)	(0.030)	(0.044)	(0.075)
Polynomial of Test Score	First order	First order	Second order	Third order
Controls	NO	YES	YES	YES
Intention To Treat Effects				
Assigned Treatment	-0.0443*	-0.0506**	-0.0577**	-0.0684**
	(0.0238)	(0.0170)	(0.0221)	(0.0267)
Observations	4019	4019	4019	4019

The impact on Drop-out



Robustness checks: Polynomial of Test Score with Interactions

	(1) Credits	(2) Credits	(3) Credits	(4) Drop-out	(5) Drop-out	(6) Drop-out
	Two-Stage Least Squares Estimates					
Effective Treatment	7.2950**	8.209**	13.537***	-0.073**	-0.091**	-0.135*
	(2.973)	(3.382)	(4.575)	(0.0301)	(0.044)	(0.074)
Polynomial Term(Order)	First	Second	Third	First	Second	Third
Observations	4019	4019	4019	4019	4019	4019

Robustness checks: Local Linear Regressions. Different Windows

	(1) Credits	(2) Credits	(3) Credits	(4) Drop-out	(5) Drop-out	(6) Drop-out
	-10/+10	-7/+7	-5/+5	-10/+10	-7/+7	-5/+5
	Two-Stage Least Squares Estimates					
Effective Treatment	10.147***	13.862***	19.797***	-0.084**	-0.118*	-0.202**
	(3.136)	(4.319)	(4.771)	(0.0367)	(0.052)	(0.069)
Observations	2055	1521	1178	2055	1521	1178

Conclusion

- We have examined the impact of remedial courses offered by an Italian University on students' performance
- To uncover the effects of remedial courses we have used a Fuzzy Regression Discontinuity Design
- From our analysis it emerges that remedial courses have a positive impact on the number of credits acquired by students during the first two years of their academic career
- The magnitude of the effect, ranging from 7 to 10 credits in most specifications, is not very large,
- considering the relevant investment of 160 hours in terms of teaching activities
- very relevant monetary costs (about 1,000 euros for each student)

Conclusion

- We find significantly larger effects as regards the probability of drop-out from university, which reduces of 7-8 percentage points for students attending remedial courses (a decrease of about 30%), suggesting that remedial courses could have an impact especially on low ability students